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Integrated Diagnostics and Time to Maintenance Estimation for Complex Engineering Systems

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Abstract - **Prognostics and Health Management (PHM) [1] is a key enabler of Condition Based Maintenance Plus (CBM+) [2]. In essence, it refers to the "Plus" by providing the ability to predict future health status of a system or component, as well as providing the ability to anticipate faults, problems, potential failures, and required maintenance actions. From the perspective of operation and maintenance (O&M) world, the vital knowledge requirements from PHM are indicators of degraded health condition (alarm, warnings, call for inspection, etc.), estimates of time to onset of such indicators, estimate of time to maintenance, and ahead-of-time diagnostics for identification of the root causes (or sources) that will likely cause these maintenance calls. Such knowledge provides lead time to the operators and system maintainers to prepare for inspection and schedule maintenance opportunistically, so as to minimize downtime and optimize maintenance cost.**

Qualtech Systems, Inc. (QSI) has developed a domain-neutral capability for tracking and trending sensor observations with considerations to operating mode changes, sensor dropouts, and measurement noise. This capability has been introduced to TEAMS® (Testability Engineering and Maintenance Systems) [3] - the health management decision-support software suite of QSI. By leveraging the built-in diagnostic features of TEAMS, this capability provides 'time-to-alarm' and 'time-to-maintenance' estimates along with the list of potential failure sources (subsystems, components, etc.) responsible for the predicted alarms and maintenance calls. A trend fusion capability has also been introduced for accurately estimating the time to maintenance for components monitored by multiple sensors exhibiting differing observation trends. Introduction of these capabilities facilitates utilization of same dependency model (TEAMS model) for reactive diagnosis and proactive identification of the components that require maintenance within a time horizon set by the operator or the maintainer. This allays the need for developing separate diagnostic and prognostic models, which in general are costly and lengthy work – and thereby offers an efficient and economic enabler for the CBM+ paradigm.

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1. INTRODUCTION

Motivation

A well-developed PHM scheme can provide decision support for

(a) System performance improvement [4]: Operating cost optimization, optimal usage, and logistics cost reduction.
(b) Safety improvement: Efficient fault detection and isolation, degradation estimation, and ahead of time indication of failures
(c) Maintenance costs reduction: Unscheduled (reactive) maintenance events reduction, faster turn-around-time, and spare-parts cost reduction.

Advanced fault detection and diagnostics (FDD), and maintenance-related decision-support capabilities (e.g., guided troubleshooting, optimal repair-replacement strategy, etc.) have contributed significantly in improving the O&M efficiency of complex engineering systems. Such efficiency can be further improved through adopting the system performance and maintenance cost reduction capabilities of PHM in the O&M paradigm.

PHM – Existing Approaches

Prognostics of engineering systems has been an active research area for quite a while, in recent time, it received attention from the industrial and commercial world as well. A variety of model-based, data-driven and hybrid methods have been developed for condition forecasting and remaining useful life (RUL) estimation. The model-based approaches utilize the system-dynamics knowledge for inferring failures/degradations and their progression from the observation residuals [5]. Data driven prognostic approaches develops the fault detection/identification and degradation-progression models from monitored data primarily utilizing regression, neural network, or fuzzy-logic based techniques [6]. The hybrid approaches utilize techniques from both model-based and data-driven world – a common trend is to utilize data-driven techniques for degradation-level estimation, and employ a physics-based degradation progression model for RUL estimation.

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PHM requires integration of diagnostics and prognostics techniques such that actionable 'health management' decisions can be made for an engineering system. Integrated diagnostics and prognostics has been addressed in some recent works. Roychoudhury et al. [8] proposed a model-based approach the uses a common modeling paradigm to model both the nominal and faulty behavior in all aspects of systems health monitoring. As for other model-based approaches, this approach also requires in-depth knowledge about system dynamics. Proportional hazards models are commonly used in reliability analysis; in recent time they are also proven useful for trending of the fault/degradation propagation process [7]. However, the assumption that the size of the effect of the exposure and other covariates on the hazard are constant over the study period and not functions of time and exposure might not hold for systems that degrade differently at different stages of their life under same loading conditions. Integrated diagnostics and prognostics approach solely based on HMM have also been proposed [11]. However, these approaches require distinct HMM models for different faults as well as for multiple levels of degradation for reliable RUL estimation – which can be impracticably large for complex systems. A scheme consisting of principal component analysis (PCA), hidden Markov model (HMM), and an adaptive stochastic fault prediction model has been proposed by Zang et. al [9]. In this scheme, a fault propagation model is used that requires information about material properties, process conditions, or environmental factors. Utilization of physics-based models in conjunction with physics-of-failure (PoF) models has also been proposed in different works. Kulkarni et al used it for DC-DC converter diagnostics and prognostics [10]. These approaches require a baseline diagnostic/prognostic model developed from the knowledge of system (or system-failure) dynamics; which, thereafter is modulated by the experimental data (or field observations).

Shortcomings Existing PHM Approaches

Different PHM approaches has their specific strengths and weaknesses [7], [12]. The previous subsection provides an overview of some current approaches in PHM and some specific issues encountered therein. The major issues encountered in developing and deploying prognostic schemes can be summarized as

- Vast Background Knowledge Requirement: Development of PHM scheme require background knowledge about a system's behavior in healthy, faulty/failed, as well as in the transition (degradation) states. Today's complex engineering systems can have large number of failure modes, they may also operate in multiple modes, their usage conditions may widely vary, and the boundaries for nominal and degraded states are decided in application/operator-specific manner. Such attributes significantly extends the breadth and depth of knowledge requirement for PHM scheme development, which in the first place is already formidable. In today's system development & production paradigm, where multiple design groups, component manufacturers, and system integrators are involved, collection and collation of such vast amount of knowledge is both laborious and costly – and such cost may outweigh the benefits of PHM.
- Narrow Application Scope: PHM approaches that have been developed for real-world usage, in general, are highly customized or tuned - prognostic models developed for one system seldom works for other similar systems (put ref.). Even version changes (where few new/modified parts are introduced) require revision of the prognostic models. Along with the need for continuous re-development, this issue also puts forward the requirement for archiving and maintaining large number of prognostic models for a single system - each applicable to a different configuration/version.
- Susceptibility to Uncertainties: Over the operating life of a complex engineering system, it undergoes maintenance, tuning and possibly, refurbishment. All of these activities changes behavior of the system. Introduction of the new or modified parts is common contributor to it; however, just disassembly and reassembly of systems for the purpose of inspection might alter the system's behavior. Thus even highly customized prognostic models are not guaranteed to provide reliable failure forecasts.
- Granularity of RUL Estimate: PHM schemes are generally concerned with providing the remaining useful life estimates at a single-level of focus – usually for the overall system. While such estimate helps the operator in maintenance scheduling, it does not provide information about the root cause(s) behind the forecasted system failure. Inclusion of such information could help the O&M world in diagnosis, troubleshooting as well as efficient resource management (e.g., technician with appropriate skills, spare parts, tools, etc.) for maintenance.

A Practical Approach to PHM

PHM is an evolving area; hence, effort for overcoming the problems with its development, deployment and adaptation in real-world scenarios are ongoing. Given the limitations in knowledge gathering and transferring, capabilities of analytic tools, and permissible time and cost for development and adaptation, a PHM approach that could be successfully inducted in the O&M world should be (a) able to be developed with the knowledge available to the O&M organizations, (b) generic enough, and has easy customizability for wide range of systems; (c) inherently immune to process noise (that may result from behavioral difference between systems of same make and models) and maintenance actions, and (d) able to identify the potential failure source(s) (along with their individual time-to-fault estimates) that drive a system to a forecasted failure. In essence, it calls for simpler - less labor and cost intensive to develop, and less demanding to user's skills, but adaptive PHM schemes.

In recent time, Qualtech Systems, Inc. (QSI) has studied the needs for PHM from the O&M perspectives, explored the potential solutions and developed an approach that utilizes domain-neutral trending algorithms in conjunction with the built-in diagnostic/analytic capabilities of their TEAMS (Testability Engineering & Maintenance System) software toolset. The approach fulfills much of the abovementioned capabilities and functionalities desired from a PHM scheme.

The background knowledge requirement for the approach is marginally higher than that for developing the diagnostic model (TEAMS model), and does not require customization from the users that necessitates high-degree of system-related knowledge. Thus this approach can be easily put to work for providing PHM decision support for complex engineering systems. In this paper, a detailed description of this approach, discussions on underlying technology, and application examples are presented.

2. TECHNOLOGY DESCRIPTION

While the generally expected outcome from prognostic schemes is the RUL, the O&M world can be better served with estimates of Time-to-Alarm (TTA) and Time-to-Maintenance (TTM). The descriptions of TTA and TTM follow:

- **Time-to-Alarm:** System monitoring schemes utilizes various tests for performance and condition assessment. Time-to-alarm refers to the expected remaining time before a 'test' fails. The 'test' might be based on simple logic, such as threshold crossing of a monitored parameter; or, more complex conditions, involving multiple parameters and a set of rules. Essentially, time-to-alarm provides the operator (and/or the maintenance organization) an indication about when to start monitoring a system more closely – and which observed parameters to focus on.
- **Time to Maintenance:** To prevent unexpected breakdown, a system should be maintained proactively. In general sense, such maintenance can be performed at any instant before the system fails. But in practice, meaningful maintenance might only be performed when the system is below some degradation threshold. Once this threshold is crossed, maintenance could become much costlier or might call for replacement of the entire system (one such example is the pad and rotor in the automotive braking system). Time-to-maintenance refers to the remaining time for reaching a significant level of degradation, beyond which, system maintenance becomes much costlier and system breakdown risk considerably increases.

In general, a system level failure event results from failures of a few (sometimes, just one) components. Additionally, there could be situations when failure of certain components do not result a system breakdown – due to low criticality, redundancy, and sparse usage of the components. Thus, for the maintainers, knowledge about TTM of individual components (or subsystems, modules, etc.) along with that of the overall system is of more value. Such knowledge provides them head-time to prepare for maintenance of specific components with proper resources. As mentioned earlier, alarms are generated on the basis of test failure(s). From the diagnostic context, test failures are ramifications of faults/failures in components or subsystems. Thus specific alarms are associated with faults/degradations in specific component(s). Hence, knowledge about TTA aids the O&M personnel in preparing for performing well-focused inspections.

Integrated Diagnostics and Time to Maintenance Estimation Approach:

QSI pursued an approach that can be easily accommodated in their TEAMS software suite. The approach uses existing diagnostic capabilities of TEAMS and newly added tracking and trending algorithms that can detect and track degradation signatures (as observed parameters) in a system. The key ideas in this approach are as follows

- Tests can be designed to detect degradation: Observations (or features extracted from observations) from health monitoring system can be associated with degradation (onset, nominal, critical value). Oftentimes, these features are closely associated with those which are used to detect hard failure. Similar test logic can be used for detection of hard failures and degradations. However, for degradation detection, the thresholds are usually needed to be lowered down compared to the hard failure cases.

- Domain and application neutral algorithms can be used to track the "degradation to fault progression": These algorithms track the trend(s) of the observations (or extracted features), and forecast them over time. The forecasted trends can be used as inputs to the degradation detection tests and TTAs could be estimated. These algorithms can be purely self-trained from the observations, and need not be pre-tuned with any domain or application-specific knowledge.

- Identify components that will reach significant degradation level within a given time interval: The many-to-many map between degradation sources (components) and tests, which is akin to the problem in diagnosis can be solved using standard diagnostic models and algorithms. The trend of fused TTA estimates from one or more degradation detection test associated with a degradation source can be used to estimate its time-to-maintenance.

In implementing the integrated diagnostics and TTM estimation capability, QSI leveraged their “minimal diagnosis” technique along with the newly developed tracking and trending technique. Short descriptions of these techniques are provided next.

Minimal Diagnosis in TEAMS

TEAMS diagnosis puts a component in either Good, Bad, Suspect or Unknown category. Here, standard diagnosis refers to the analysis that declares only the uniquely isolated failure sources (or modules) as Bad; all other failure sources covered by one or more ‘failed tests’ are declared as ‘suspects with ambiguities’. In case of minimal diagnosis, the failure sources within a suspect set that can completely explain the related test signature are identified and those are assigned to the ‘minimal category’, the remaining are treated as ‘residuals’. In essence, those identified as minimal are likely the (or definitely - when the standard diagnosis had no suspect) “Bad” failure sources, whereas those identified as Residuals are the less likely suspects. The concept is explained by an example illustrated through Figure 1 and

Table 1. It should be noted that, for this example, when only one test outcome is reported, the other is assumed unknown. This is especially important for time to maintenance analysis, as for a large ambiguity group, preparation for maintenance would likely be less expensive compared to the more elaborate and expensive combination of highly probable Bad failure sources and less probable Residuals.

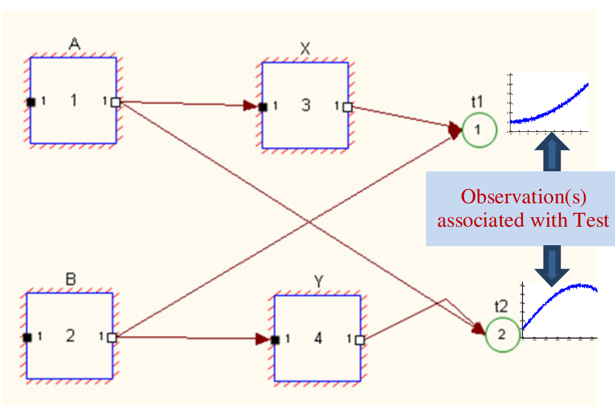

Figure 1: Minimal Diagnosis – Example Model

Table 1: Standard to Minimal Diagnosis

	Test Outcomes	Standard Diagnosis		Minimal Diagnosis	
		Bad	Suspects	Minimal	Residual
1	All fail		A, B, X, Y	{A, B}	-
2	t1 fail		A, B, X	-	A, B, X
3	t2 fail		A, B, Y	-	A, B, Y
4	t1 fail, t2 pass	X		X	-
5	t1 pass, t2 fail	Y		Y	-

Additionally, the minimal diagnosis approach provides a list that tells which fault(s)/degradation(s) explains which test(s). This allows identification of redundant tests (if any). When redundant tests are present, a subset of them could be disregarded for computing the TTM if the trends of the observations (that are associated with those tests) widely diverge from the other tests explaining the same degradations. For the example model (see Figure 1), if both t1 and t2 fail, then the time to maintenance for A and B will be computed from the fusion of individual time to maintenance estimates of t1 and t2; in all other cases, time to maintenance estimates from either t1 or t2 provides the time to maintenance for the components under minimal or residual categories.

Trending and Tracking Algorithm

Several types of tracking and trending algorithms can be used to track the progression of degradation in engineering systems. Kalman Filter-based [18]. Time Series Regression-based [14], and Neural Network Regression-based [15] algorithms are commonly used for tracking and trending. Techniques like Moving Average Filters [19], Smoothing Splines [19], α-β Filter, Approximate Moving Horizon Estimation (MHE) [20], and Hodrick-Prescott Filtering [21], Monotonic Regression and L_1 – filtering [22] are widely used for trend modeling in economic and financial domains, and can be used in engineering applications as well.

Owing to the simplicity, robustness, and feasibility for embedded implementation, QSI selected a Kalman Filter (KF)-based algorithm [18]. However, the algorithm is modified and tuned in such a way that instead of tracking individual samples it tracks the trend of the observations (or extracted features). It has also been augmented with the following features

- Adaptive to gradual shifts to system behavior and estimates most of the model parameters from the data
- Built-in constraints ensure prevention of erroneous estimates resulting from
  - Large swings
  - High degree of jitter
  - Mode changes (or possible replacement of parts)
- Determines when the estimates are reliable, and stops reporting estimates when there is a misfit
- Allows the user to define time horizons for maintenance - prevents reporting maintenance time that has no practical use or significance.

Incorporation to TEAMS

A PHM capability only becomes meaningful when it is made available to the user in a realistically usable way. The TEAMS software toolset is a well-developed, matured and widely accepted means for diagnostic modeling and analysis. Thus for QSI, it has been a natural choice to incorporate the capability in the TEAMS software toolset.

The integrated diagnostics and TTM estimation approach requires a diagnostic model (test-fault dependency model), diagnostic algorithms for efficient identification of the faults/failures subject to the test outcomes, minimal diagnosis algorithm, and the trending and tracking algorithm. Except for the last item, others are already resident to TEAMS. TEAMS models employ ‘tests’ whose outcomes indicate ‘presence’ or ‘absence’ of some conditions or phenomena or events using user defined test logic (analytic relations or algorithms). QSI opted for introducing the trending and tracking algorithm as ‘test logic’. The outcomes for existing tests in TEAMS are binary, whereas for trending and tracking the test outcomes need to be continuous numbers; hence, a new type of test - ‘degradation detection test’ were also introduced. More detailed description of this type of tests is provided in the Application Example section.

3. Application Examples

QSI has tested the integrated diagnostics and TTM estimation approach with a wide range of simulated cases, and thereafter with real-world systems. In this section, an application example using a simple system, and a real-world application case involving electromechanical actuation (EMA) systems are presented.

Illustrative Example

A simple example case was constructed in TEAMS and simulation data was generated to verify the feasibility of the approach. Discussions on this feasibility study addressing the model, data and results are provided next.

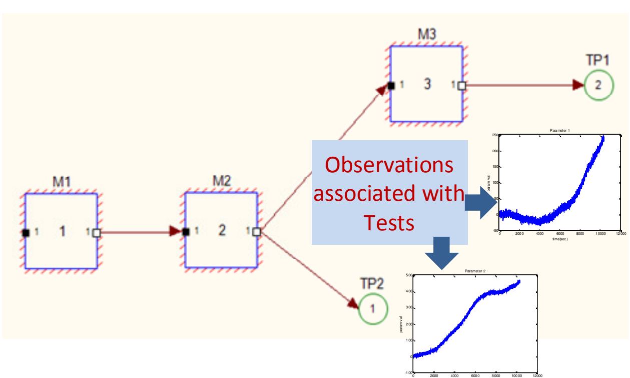

Figure 2: Illustrative Example System for Maintenance Forecast

The TEAMS model of the system is shown in Figure 2. Observations (measured parameter values) for the tests T1 (under the test point TP1) and T2 (under the test point TP2) are also shown in the figure. The Standard and Minimal diagnostic results for this system are shown in Table 2[1]. Each test point hosts two tests, one for Degradation, and the other one for Hard Failure. For instance, in the actual model the tests under TP1 are, T1_Maint and T1_Hard that represents the maintenance and hard failure tests, respectively. For the sake of simplicity, here we mention T1_Maint and T2_Maint as T1 and T2, respectively. The maintenance tests are designed with two thresholds: the lower one is the Degradation/Yellow threshold – whose crossing indicates that the module has entered degradation stage; the upper one is the Alarm/Red threshold – whose crossing indicates that the module has entered significant/critical degradation stage and maintenance should be performed.

Table 2: Standard to Minimal Diagnosis for Illustrative Example

	Test Outcomes	Standard Diagnosis		Minimal Diagnosis	
		Bad	Suspects	Minimal	Residual
1	All fail		M1, M2, M3	M1	-
2	T1 fail		M1, M2, M3	-	M1, M2, M3
3	T2 fail		M1, M2	-	M1, M2
4	T1 fail, T2 pass	M3		M3	-
5	T1 pass, T2 fail	Invalid Cond.	Invalid Cond.	Invalid Cond.	Invalid Cond.

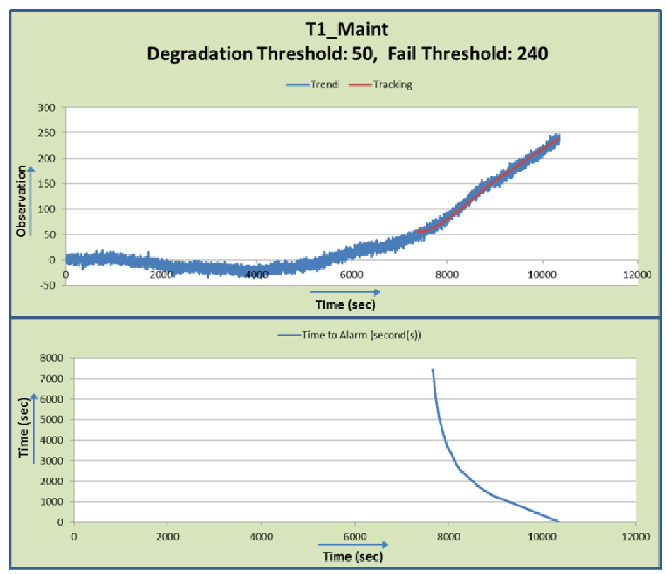

Figure 3: Time to Alarm Estimates for T1

[1] It should be noted that, for this example, when only one test outcome is reported, the other is assumed unknown.

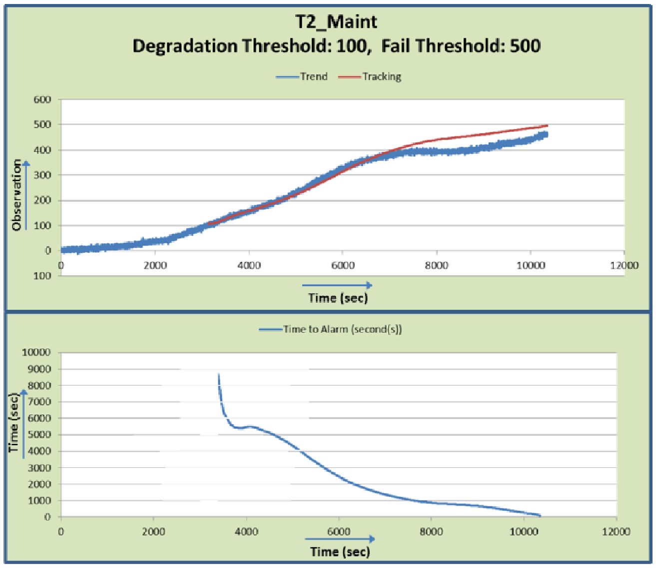

Figure 4: Time to Alarm Estimates for T2

In this study the Yellow thresholds for T1 and T2 were 50 and 100, respectively; whereas the Red thresholds for T1 and T1 were 265 and 500 respectively. The time to alarm estimates for T1 and T2 are shown in Figure 3 and Figure 4, respectively. A partial view of the Tracked values of the observation associated with T2_Maint test and the corresponding TTA is shown in Table 3.

Table 3: Tracking and TTA Estimate for T2

Time (sec)	Observation		TTA (sec)
	Trend	Tracked	
3571.9	136.27	131.23	6065
3573.1	125.66	131.26	6061
3574.3	130.27	131.32	6056
3575.2	134.98	131.41	6051
3575.8	135.99	131.48	6046
3576.9	132.02	131.56	6042
3578.6	130.66	131.66	6037
3579.8	140.87	131.81	6032
3580.4	132.03	131.85	6027
3582	132.7	131.95	6022
3582.9	146	132.11	6017
3583.6	128.06	132.12	6012
3585.1	136.61	132.25	6007
3585.7	138.48	132.33	6001
3587.2	130.22	132.41	5996
3588.3	129.9	132.46	5991

The time to maintenance estimates for the system is shown in Figure 5. For this example system, only Situations 1, 3 and 4 (as presented in Table 2) were observed. Consequently, the TTM for M1 and M2 has been estimated from the TTA estimate of T2 solely; whereas, the TTM for M3 has been estimated by fusing the TTA estimates of T1 and T2.

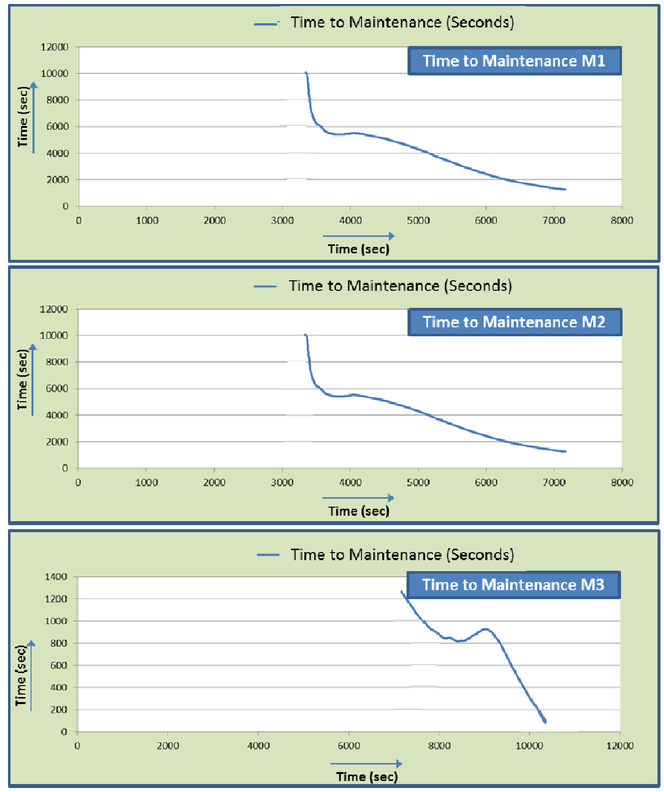

Figure 5: Time to Maintenance Estimates for the Illustrative Example System

Diagnostics and TTM Estimation of EMA Systems

Under a recent Air Force project, QSI in collaboration with Lockheed Martin Co., and Moog Inc. developed a PHM scheme for EMA Systems. The scheme leveraged the integrated diagnostics TTM estimation approach discussed in this paper. A brief discussion of the work presented in this subsection (details of this work can found in [13]).

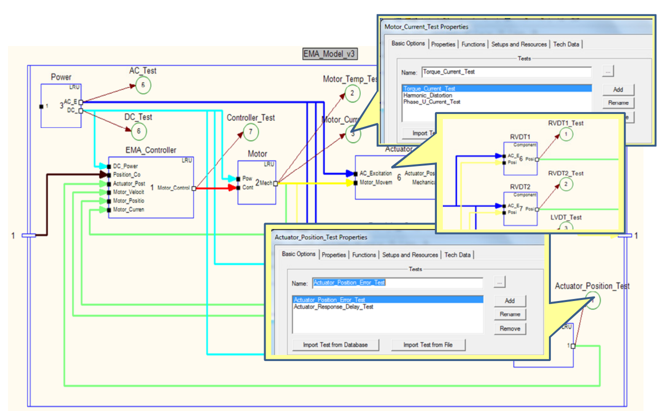

Figure 6: A Screenshot of Diagnostic Model of an EMA in TEAMS

The major components of an EMA system are the electric motor, EMA controller, motion a collection of gears and bearings, rotary-to-linear motion converter, lubrication systems, resolver and motion sensors. QSI utilized information from Moog Inc., and public domain to develop a dependency model (TEAMS model) of the EMA (see Figure 6). The model comprised of 60 failure modes in 10 line replaceable units (LRUs), and 13 tests – of which, 2 were degradation detection tests.

NASA conducted a range of degradation experiments using their FLEA Testbed [17]. The experiments were performed on Ultra Motion Bug Linear Actuators. A part of the data has been made publicly available through the DASHLink [16] website. A subset of this data was utilized for characterization of healthy EMAs and identifying trending degradation trends over time. Data from FLEA experiments that were used in this work came from a dataset with a large collection of motion and load profiles. Data was collected at both low (100Hz) and high (20 KHz) sampling rate. The high sampling rate data was collected only for the first 30 sec of the experiments. The lower sampling rate data covered 21 parameters (listed in Table 4), whereas the higher sampling rate data covered 6 parameters.

Table 4: Monitored Parameters from the FLEA Testbed Experiments

Load Cell	Motor X Current
Ambient Temperature	Motor Y Current
Motor X Temperature	Load Motor Current
Motor Y Temperature	Motor X Voltage A
Motor X Nut Temperature	Motor X Voltage B
Motor Y Nut Temperature	Motor Y Voltage A
Load Motor Temperature	Motor Y Voltage B
Load Actuator Position	Desired Load
Actuator X Position	Test Actuator Duty Cycle
Actuator Y Position	Load Duty Cycle
Desired Position	

QSI used NASA's FLEA Dataset and the TEAMS model of the EMA for Diagnostics, TTA and TTM estimation. Owing to the extended coverage and duration, the low sampling rate data was used. Preliminary studies showed that Motor Temperature, and statistical features Motor Torque (in relation to commanded displacement), and Relative Position Errors are the useful features for degradation detection and tracking for this specific EMA system. Hence, the input data for degradation tracking tests consisted of these features. Based on the literature surveys the degradation and fail (maintenance) thresholds were assigned.

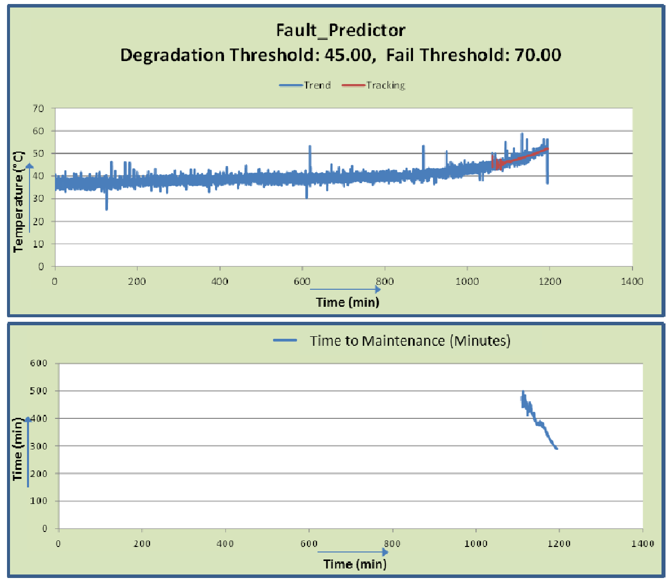

Figure 7: Time to Alert for Motor Fault Predictor Test

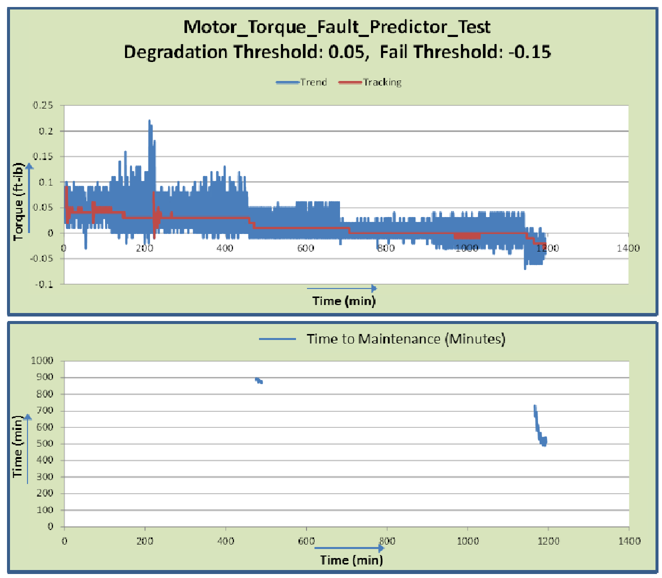

Figure 8: Time to Alert for Motor Torque Fault Predictor Test

The results of degradation detection, tracking, and TTA for Motor Fault, and Motor Torque Fault are shown in Figure 7. This scenario only used two degradation-type tests, Motor Fault Test, and Motor Torque Fault Test. Consequently, the ambiguity group-size was large - 4 LRUs (Motor, Actuator, Demodulator, and Resolver) out of 6 LRUs in the TEAMS model were identified as suspects. However, the time-to-maintenance profile for the Motor (actual source of degradation) differed from that of the other 3 LRU in the suspect group. This difference resulted from the different coverage of the tests used for this scenario. The time to maintenance estimates for the suspects are shown in Figure 9. Since the physical system under the experiment was not driven to failure, the TTM estimates are more of demonstration of analytic capability, rather than real-world proof.

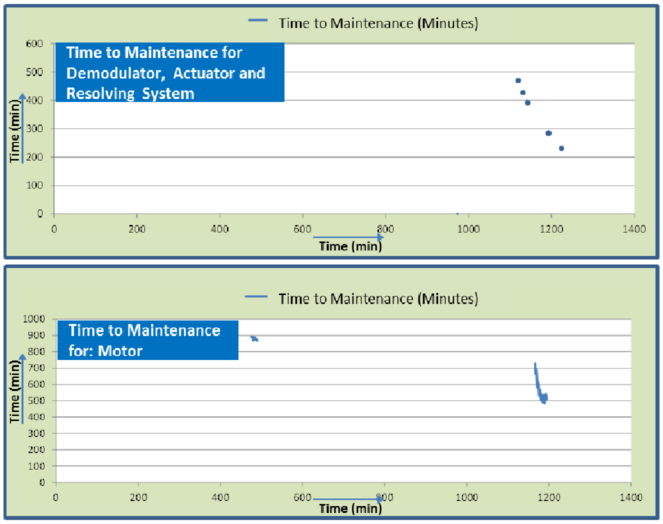

Figure 9: Component Level TTM Estimates

4. CONCLUSION

QSI has developed an approach for facilitating PHM through integrated diagnostics and time-to-maintenance estimation. The approach leverages efficient diagnostic algorithms, along with domain-neutral trending tracking and forecasting techniques. Being less demanding about domain knowledge and information about target system, the approach is practical and suitable for utilization in PHM of complex real-world systems. The approach has been software implemented and incorporated into QSI's TEAMS software toolset. Incorporation in TEAMS, a well-established and user friendly diagnostic modeling and analytic tools paves the way for utilization of the approach in real-world applications.

ACKNOWLEDGMENTS

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REFERENCES

[1]. Zeng, S. K., Pecht, M. G., & Wu, J. (2005). Status and Perspectives of Prognostics and Health Management Technologies. ACTA AERONAUTICA ET ASTRONAUTICA SINICA-SERIES A AND B-, 26(5), 626.

[2]. Iung, B. (2012, May). Overview on E-maintenance facilities addressing PHM vs. CBM+ requirements. In International Conference on Prognostics and Health Management, IEEE PHM 2012.

[3]. Product Webpage of Qualtech Systems, Inc. http://www.teamqsi.com/products/

[4]. S. Kumar, M. Torres, Y. C. Chan, and M. Pecht, "A hybrid prognostics methodology for electronic products", IEEE International Joint Conference on Neural Networks 2008.

[5]. J. Luo, M. Namburu, K. Pattipati, L. Qiao, M. Kawamoto, and C. S. Chigusa. "Model-based prognostic techniques [maintenance applications]." AUTOTESTCON 2003. IEEE Systems Readiness Technology Conference, pp. 330-340. IEEE, 2003.

[6]. Hack-Eun Kim, "Machine Prognostics Based on Health State Probability Estimation," PhD Thesis – Faculty of Built Environmental Engineering, Queensland University of Engr. and Tech., 2010.

[7]. A. K. S. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," Mechanical Systems and Signal Processing, vol. 20, pp. 1483-1510, 2006.

[8]. Indranil Roychoudhury and Matthew Daigle, "An integrated model-based diagnostic and prognostic framework." Proceedings of the 22nd international workshop on principles of diagnosis. 2011.

[9]. Xiaodong Zhang, Roger Xu, Chiman Kwan, Steven Y. Liang, Qiulin Xie, and Leonard Haynes, "An integrated approach to bearing fault diagnostics and prognostics." In American Control Conference, 2005. Proceedings of the 2005, pp. 2750-2755. IEEE, 2005.

[10]. Chetan Kulkarni, Gautam Biswas, Xenofon Koutsoukos, Jose Celaya, and Kai Goebel, "Integrated diagnostic/prognostic experimental setup for capacitor degradation and health monitoring." In AUTOTESTCON, 2010 IEEE, pp. 1-7. IEEE, 2010.

[11]. Pundarikaksh Baruah, and Ratna B. Chinnam, "HMMs for diagnostics and prognostics in machining processes." International Journal of Production Research 43, no. 6 (2005): 1275-1293.

[12]. M. Schwabacher, "A Survey of Data Driven Prognostics," in AIAA Infotech@Aerospace Conference 2005.

[13]. Mohammad Azam, Sudipto Ghoshal, Dan Taylor, Tony Chirico III, Earl Gregory, "Prognostics and Health Management of Electromechanical Actuation Systems for Next-Generation Aircraft," In proceedings of AIAA Infotech@Aerospace Conference, August 21, 2013

[14]. L. Ljung, "System Identification: Theory for the User," Prentice Hall Inc., NJ, USA, 2nd Edition, 1998

[15]. Warren S. Sarle, "Neural networks and statistical models," In Proceedings of the Nineteenth Annual SAS Users Group International Conference 1994, pp. 1538–1550.

[16]. Information and data on FLEA Testbed from DASHLink website: https://c3.nasa.gov/dashlink/projects/45/resources/

[17]. Balaban, E., Saxena, A., Narasimhan, S., Roychoudhury,I., Goebel, K., & Koopmans, M., "Airborne Electro-Mechanical Actuator Test Stand for Development of Prognostic Health Management Systems," Proceedings of Annual Conference of the PHM Society 2010, October 10-16, Portland, OR

[18]. Yaakov Bar-Shalom, X. Rong Li, and Thiagalingam Kirubarajan, "Estimation with Applications to Tracking and Navigation," John Wiley & Sons, 2001

[19]. Blanchi, M., Boyle, M., Hollingsworth, D., 1999. A comparison of methods for trend estimation. Applied Economics Letters, 6, 103–109.

[20]. Haseltine, E.J.; Rawlings, J.B. (2005). "Critical Evaluation of Extended Kalman Filtering and Moving-Horizon Estimation". Ind. Eng. Chem. Res. 44 (8): 2451–2460.

[21]. Hodrick, R. J. and E. C. Prescott (1997), Postwar US business cycles: an empirical investigation, Journal of Money, Credit, and Banking, 1-16.

[22]. S.-J. Kim, K. Koh, S. Boyd, and D. Gorinevsky, "L1trend filtering," SIAM Review, vol. 51, no. 2, pp. 339–360, 2009.

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